STRUCTURE - PROPERTY RELATIONSHIP OF PARTICULATE COMPOSITES: MACHINE LEARNING APPROACH

A SYNOPSIS

Submitted by

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1. INTRODUCTION

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it [1]. Microscopic images are used in material science for imaging the materials and its types Optical Microscopic, Scanning Electron Microscopic (SEM) and Transmission Electron Microscopy (TEM). It helps to understand the strength and applicability range of the material [2,3]. Scientifically, The Material science research is playing a vital role in various aspects of fields. The demand of good and quality material is increasing day-to-day. The imaging of materials is done by Optical Microscopic images. The need of material science requires two important purposes 1) Design of new material 2) Predict and avoid failure. Mostly microscopic images gives the result as qualitative analysis of the material not in the form of quantitative. The quantitative analysis done only by microstructure. The Optical Microscopic microstructural analysis helps to predict the materials behaviour and strength [4]. Materials behavior can not be understood without characterizing microstructure because it is always heterogenous. Only statistical representation of microstructure predicts the performance of materials [5]. The different microstructural features in terms of size, shapes, position or orientation. For statistical analysis of Microscopic images an automated image analysis method is in demand. It is developed using Python. Since some tools are available such as Dream 3D and ImageJ but it is working for certain objects only and not provide statistical correlations.

For analysing general microstructures of Optical Microscopic images a newly automated method hsa been developed. For statistical analysis machine learning algorithms are employed in the newly developed image analysis automated method. Machine learning is getting more attention among the researchers in all fields. Image processing techniques can be applied in all the aforementioned applications, involving various algorithms in machine learning [6-9]. Amongst, k-means algorithm and Density-based Spatial Clustering of Application with Noise (DBSCAN) are predominantly used in machine learning and is most suitable for our proposed work DBSCAN is a density-based clustering technique where clusters are identified by looking at the density of points. K-means clustering algorithm is helps to solve the clustering data points such as choosing k values and minimize the variance in each cluster [10-12]. Mostly k values predicted by elbow and silhouette method.

Currently most of the reported work says Microscopic image analysis were done by hands so it takes so many days to complete the process and the same time result

is qualitative. From statistical analysis the user can predict tensile strength of material in earlier stage itself so that failure can be avoided. The automated method results can be assessed quantitative particle dispersion in Optical Microscopic And its effect on Mechanical Properties.

2. LITERATURE REVIEW

Image Processing Techniques has gained many attentions among the researchers, due to its cost effectiveness and the scope of providing data according to the user requirement. Hongfu Xie et al. [13] proposed that the Optical Microscopic images gives subatomic resolutionTaken the distorted images as input. The restoration algorithms help to compute motion characteristics of Optical Microscopic images. Finally, the proposed methodology given better result in restore the motion distorted scanning images. The demerits of proposed work brought errors of the motion equation increases cumulative over time. Jing Su and Jing Li [14] described that in optical material science many Optical Microscopic were used. An automatic analysis method was developed as auto adaptive and automatically analyze Optical Microscopic images. This automated method helps to analyze the preprocess within few minutes instead of few days. To describe images a novelty training process was carried to capture and datasets with physical images with the help of visual computer. Mihai-Virgil Nichita et al. [15] proposed for clustering two algorithms. First one is k-means clustering and second one is fuzzy c-means technique (FCM). Here brain computed tomography image analysis were taken. K-means clustering algorithm helps in multidimensional space and found number of clusters is required. Clusters which help to found similar characteristics. The number of clusters were not defined prior so used as trial and error based. Finally k-means clustering algorithm provides a better solution in the analysis of brain images and also provided the accurate results for minimal amount of data. Yo-Ping Huang et al. [16] described Parkinson's disease (PD) MRI images were analyzed. K-means clustering algorithm and fuzzy information gain (FIG) methodology were used for analysis and visualization patterns. The FIG quantifies the fuzzified pixels where k-means used to cluster the fuzzified pixel information. The segmentation was done in MRI using hybridization of FIG and K-means clustering. The similar and unsimilar clusters based on the distance of FIG information are identified using k-means clustering algorithm.

2.1 RESEARCH PROBLEM

From the detailed literature survey, it was found that

- Mostly qualitative observations were found on the microscopic studies used in the field of polymer composite material system to correlate structure-property relationship.
- Qualitative analysis can exhibit only a macroscopic findings rather than the contribution of particle distribution on the failure mechanism of material system.
- Qualitative analysis is observed for particular microstructure features not for general. So, it is not able to predict accurate material strength of polymer materials and not able to determine the material performance in application.

3. OBJECTIVES

The main objectives of this research work are

1. To develop an automated generalized algorithm using Modified K-Means Clustering for the quantitative microstructural analysis (shape, size and Particle distribution)of Particulate Reinforced Polymer Composite (PRPC) microscopic images.
2. Develop a statistical model to predict the mechanical properties (RoM, Volume Fraction and agglomeration effects on mechanical) for different particulate polymer composites microscopic images.
3. To analyze best edge detection using various suitable algorithms for particle orientation from microscopic images.
4. To estimate the tensile strength with the effect of particle orientation in microscopic images using Adaptive Density-based Spatial Clustering of Application with Noise (ADBSCAN) algorithm.

4. RESEARCH METHODOLOGY

4.1 To develop an automated generalized algorithm using Modified K-Means Clustering for the quantitative microstructural analysis of Particulate Reinforced Polymer Composite (PRPC) Microscopic Images.

This work explored the importance of quantitative observation through imaging methods of optical and electron microscopies on the mechanical properties of particulate polymeric composites. Here we taken input Microscopic Images as Egg

shell powder (ESP) reinforced polypropylene carbonate (PPC) polymeric composites with different filler percentage weight (wt.%) from 1 to 5 wt.%. The Figure1 explains a cost-effective an automated image analysis method was developed with Graphics User Interface (GUI) option to extract black particles from the original optical images. Image segmentation is employed to assign a label for every pixel of the image. During this process, the optimal image can be reproduced based on its originality by controlling the threshold values from 0.1 to 0.6 in real time situation.

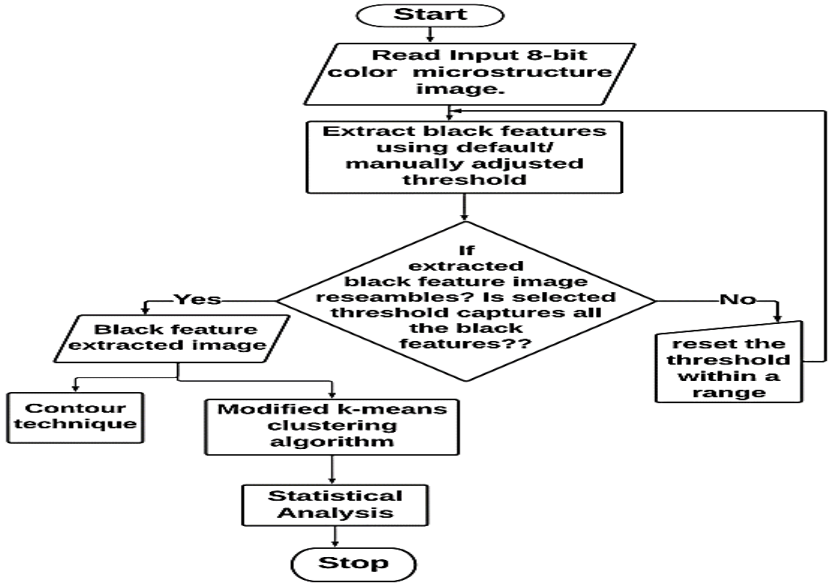
Start
Read Input 8-bit color microstructure image.
Extract black features using default/ manually adjusted threshold
If extracted black feature image reseambles? Is selected threshold captures all the black features??
Yes
No
Black feature extracted image
reset the threshold within a range
Contour technique
Modified k-means clustering algorithm
Statistical Analysis
Stop

Figure 1: Step-by-Step Process of Proposed Image Analysis Method.

The automated method was compiled with modified k-means clusterting and contour techniques. Contour technique is a process in which a curve joins all the contour points to accommodate all the pixels inside the boundary. Using one dimensional (1D) Gaussian distribution analysis, the authentication of the particle distribution data was studied and linked to the tensile strength of the composites. Tensile strength of the ESP reinforced polypropylene carbonate (PPC) polymeric composites was investigated for differing wt.% of the filler reinforcement. The automated image method for different wt.% (a) 5%, (b) 10%, (c) 15%, (d) 20% and (e) 25% fillers with optimal threshold values 0.6, 0.6, 0.45, 0.45 and 0.4.The findings indicated the tensile strength were increseased for certain wt.% but suddenly it decreased due to the presence of aggolomeration. In order to find the relationship between the wt.% of fiber and the statistical parameteres with the tensile strength of the composites, a linear regression

equation was derived and solved for the constant coefficients with the coefficiant of correlation R = 0.93 and standard error value as 3.5% which is expressed in equation 1.

$$Y=A+BX_1+CX_2+DX_3 \quad (1)$$

Where, A,B,C and D are the constant coefficients and X_1= weight percentage of filler , X_2= Mean value of the left side gaussian distribution and , X_3 = Mean value of the left side gaussian distribution.

4.1.1 Results and Discussions

4.1.1.1 Modified K-means Clustering algorithm

In classical k-means clustering algorithm the user has to find k values by a method such as elbow and silhouette. A user has to find again and again for correct 'k' clusters. In modified k-means clustering, k values found by the pixel value. The scale bar mentioned in the image will be converted into the number of pixels within the area of scale bar which can vary based on the magnification of the input images. Each pixel is assumed as square lattice with the length of "a' to cover the area of the scale bar present in the microscopic image. From modified k-means it initial stage itself the user get accurate k values required to form the clusters. Then the side of the pixel can be found out using the following relations which is inherently built-in automated analysis method which is shown in Figure 2. For an example, a total number of 105 pixels were obtained to be occupied in the reference scale of 200 μm scale.

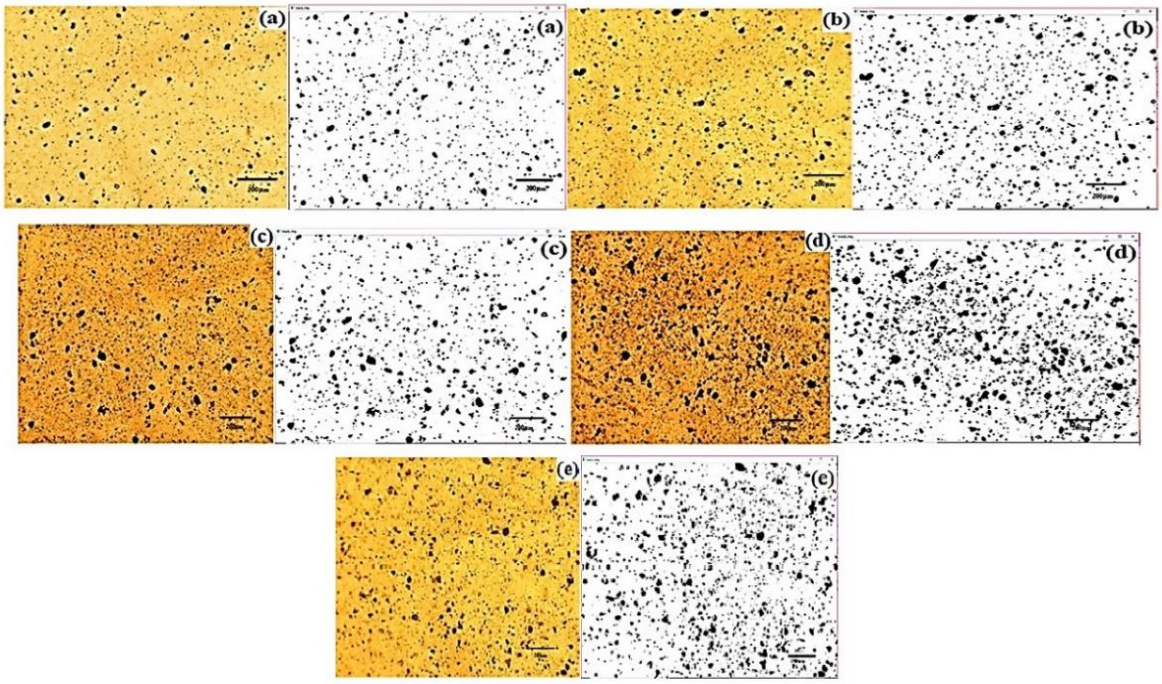

Figure 2: ESP extracted particle images for different wt.% from 1 to 5.

4.1.1.2 One dimensional Gaussian distribution statistical analysis

Figure 3 explains that modified k-means clustering algorithm was used to process Gaussian normal distribution results. Consequently, the results were primarily divided into two clusters dependent on the reference of the centroid values obtained for each cluster. Finally, the average values for both the left and the right categories were defined and plotted as a separate distribution.

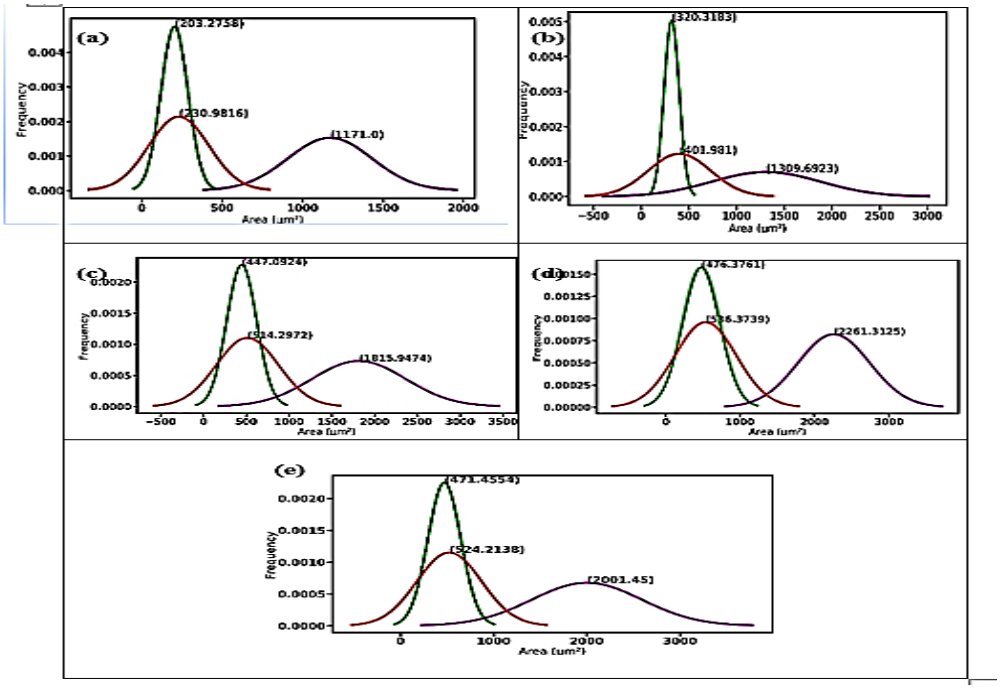

Figure 3: 1D Gaussian plot distribution for ESP reinforcing filler of 1 to 5 wt.%

4.1.1.3 Tensile Strength Analysis

The comparison results of experimental and predicted models are shown in Figure 4. If the particle distribution is even means the tensile strength were good in material. So that material is strong and the life span is long. Suppose if the material started to form agglomeration the material is weak as well as life span is very less.

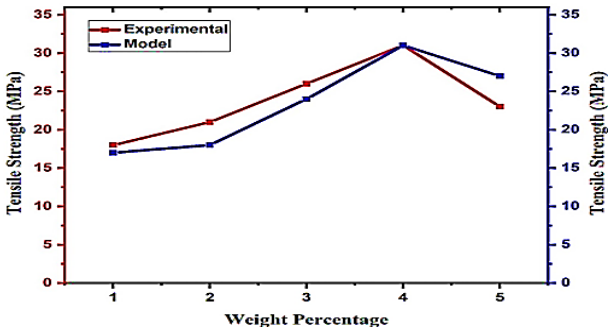

Figure 4: Comparison of tensile strength between experimental result and predicted model results

In our case in 1% weight the materials black particle distribution is even after that the additional filler composites were added upto 4 % wt. the materials tensile strength is strong but in 5% weight it started to form agglomeration. The user has to analyse the tensile modulus for long days but in our automated method we found the tensile with in few milliseconds in accurately.

4.2 Develop a statistical model to predict the mechanical properties (RoM, Volume Fraction and agglomeration effect) for different particulate polymer composites microscopic images

The input microscopic image is selected for the analysis is spent coffee bean powder (SCBP) Polymer Reinforced Particulate Composites (PRPC) with differing wt.% (5%, 10%, 15%, 20% and 25%) of the filler. The statistical result analysis are directly influenced in the mechanical properties. The mechanical properties are rule of mixture, volume fraction of filler material and agglomeration effect. In microscopic images SCBP black particles were extracted by setting intensity threshold value (0.3 to 0.45) of different wt.% by automatic mechanism. After the extraction of black particle, the modified k-means clustering algorithm is employed to find statistical analysis which is elaborately explained in 4.1. Detailed statistical analysis of the microstructural images are revealed and how it is influenced in mechanical properties. To quantify the degree agglomeration and heterogeneity in the microstructure properties were

(i) clusters number density (N_c).

(ii) dispersion factor (d_f).

Increase in the filler content increases the probability of agglomeration and sometimes leads to the coalescence of clusters, thus reducing the total number of clusters. The dispersion factor quantifies the heterogeneity in the microstructure. It is defined as the ratio between the mean area (μ) of the particles/clusters and the standard deviation (σ). Overall, these two measures, i.e., clusters number density and dispersion factor, explain the experimentally observed non-monotonic dependence of filler content on the mechanical properties of the composite material.

The detailed statistical analysis of the microstructure and the proposed effective volume fraction helps to develop a deeper quantitative understanding of the PRPC than the conventional qualitative correlation of microstructural features with the properties and failure processes.

4.2.1 Mechanical Properties

Rule of Mixture (RoM) : It is one of theoretical models where widely used to predict the composite materials' structural properties, like tensile strength using the weighted contributions from the matrix and filler material.

According to RoM the following assumptions are followed

a. Matrix is homogeneous.
b. Filler particles are distributed uniformly.
c. The properties of composite material exhibit linear dependency on the volume fraction of filler.

RoM is commonly used to quantify the properties of composite materials. In that, the strength of the composite material is calculated using the strength of individual constituting materials (matrix and filler), and it is written as,

$$\sigma_c = (1 - V_f)\sigma_m + V_f\sigma_f \quad (2)$$

Here, σ_c, σ_m and σ_f denotes the strength of the composite, base matrix and filler reinforcement, respectively. V_f represents the volume fraction of the filler material.

The tensile strength is very important to analyze the materials behaviour. From the black particle extraction through intensity threshold and Gaussian distribution given the result as RoM is overestimated such as the matrix is non-homogenous and the filler particles not evenly distributed during the wt.% increase in addition of filler and certain point the tensile strength is observed non-monotonic. RoM is employed with both the actual and effective volume fraction of the particles. The volume fraction usually calculated from traditional RoM but in this developed effective volume fraction is employed to quantify the tensile strength of the composite material . It is calculated from the weight fraction using the following expression:

$$V_f = \frac{w_f}{w_f + (1 - w_f)\left(\frac{\rho_f}{\rho_m}\right)} \quad (3)$$

Where w_f is the weight fraction of the filler material. ρ_f and ρ_m are the mass density of the filler and matrix, respectively.

4.2.2 Results and Discussions

4.2.2.1 Statistical analysis of particles distribution

For all the cases (a to e), the clusters number frequency decreases with the size of the particle/cluster area. At the same time, the particle/cluster area range increases with an

increase in the filler wt.%. For example, in the 5% case, the area ranges up to 412 μm^2, whereas the particle/cluster area can be as high as 2638 μm^2 in the 25% case. It confirms the increase in agglomeration propensity with the filler content.

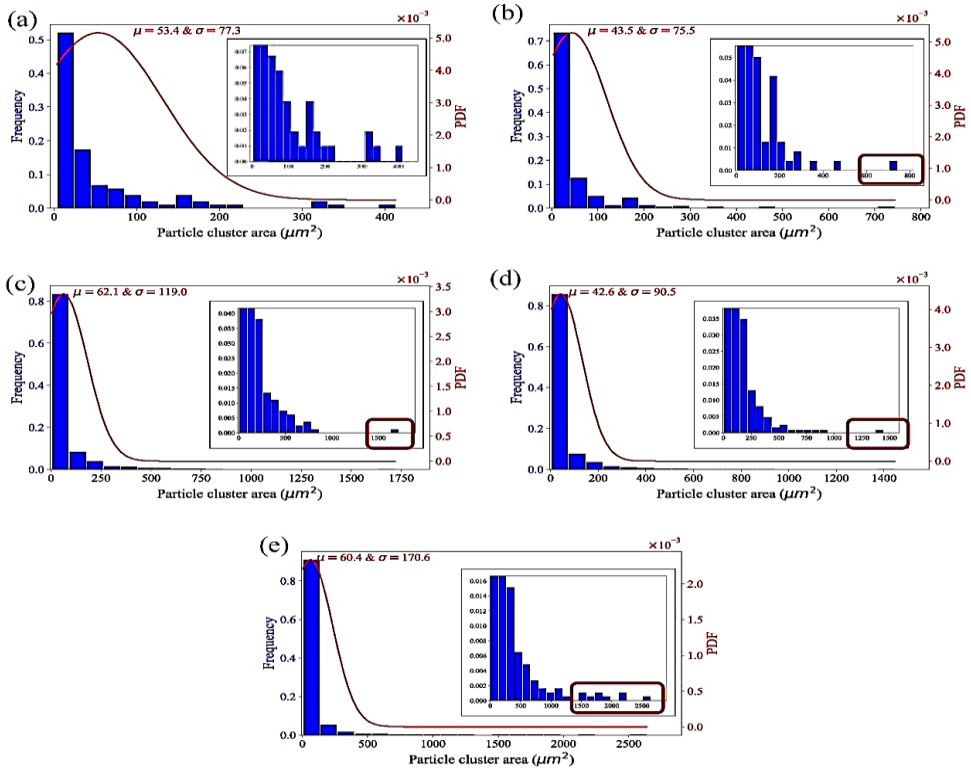

Figure 5*:* The distributions of SCBP particles and its clusters in PPC based composite films with (a) 5%, (b) 10%, (c) 15%, (d) 20% and (e) 25%.

Figure 5 clearly reveals that the blue histogram shows the frequency distribution of the particle cluster size. The red curve is the fitted Gaussian distribution to the data. The corresponding mean and standard deviation of the data are given. The enlarged view of the frequency distribution is shown in the inset, and it reveals the formation of 'clustering of clusters'. the particle/cluster area distribution is heterogenous and exhibits a bimodal distribution.

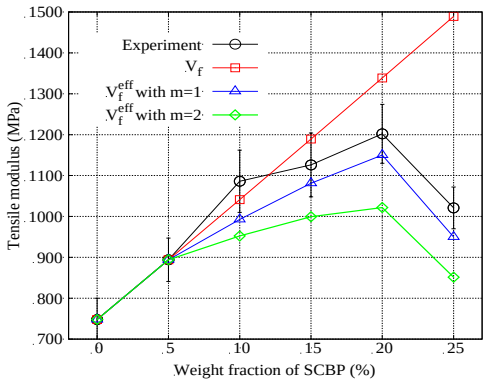

Figure 6: Model calculated and experimentally measured tensile strength

A microstructure-sensitive effective volume fraction is proposed to account for the effect of agglomeration on mechanical properties. This effective volume fraction within the rule-of-mixture model correctly captures the effective contribution of filler content on tensile which is shown in Figure 6. The automated method statistical results proven the assumptions of mechanical properties are wrong and are not valid for the actual material system wherein the filler distribution is not uniform, and the structural properties are non-linear.

4.3 To analyze best edge detection using various suitable algorithms for particle orientation from microscopic images.

Edge Detection is very important part in image Processing. It helps in providing a clear vision of boundaries in images. Significant features can be extracted such as corners, lines and curves. The four steps of Edge detection are Smoothing, Enhancement, Detection and Localization.

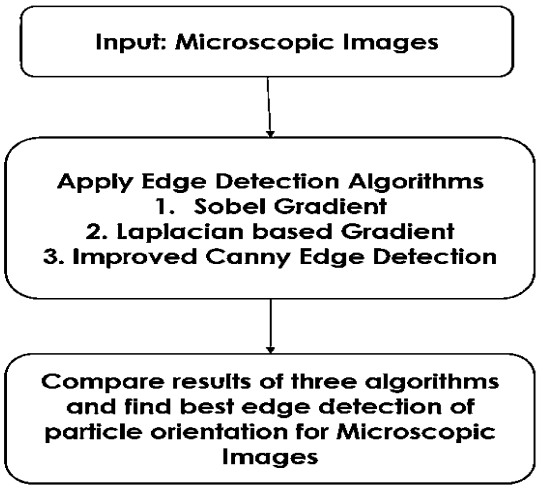
Input: Microscopic Images
Apply Edge Detection Algorithms
1. Sobel Gradient
2. Laplacian based Gradient
3. Improved Canny Edge Detection
Compare results of three algorithms and find best edge detection of particle orientation for Microscopic Images

Figure 7: Workflow of Edge Detection

Smoothing helps in reduction of noises. Enhancement sharpens the edges of the images. Detection finds the edge pixels which requires or not. Localization extracts the correct location of edges.

Various edge detection algorithms are available but chosen three important algorithms such as Sobel, Laplacian, and Improved Canny Edge Detection. Our work to find out which is best algorithm based on different parameters such as accuracy, reduction in noise level and speed of execution time (in seconds). Figure 7 explains the workflow of edge detection in Microscopic Images orientation analysis.

4.3.1 Improved Canny Edge Detection

The edge detection process identifies the edges, curves, and boundaries of objects in a digital image with the change in image brightness. In the proposed framework, ICED is utilized to detect the edges in the Microscopic Images. ICED is an edge detection approach that utilizes a multiple-stage algorithm for detecting a broad range of edges in images. With the help of this technique, useful structural information is extracted from different objects, and the amount of data to be processed is reduced. Initially, ICED uses the Gaussian function (GF) for image smoothening and calculates the gradient magnitude and direction for image de-noising. After that, to obtain a unilateral edge response, non-maximum suppression according to gradient direction is calculated. At last, the double threshold model is adapted for detecting and connecting the edges. The ICED steps are discussed further.

4.3.4.1 Gaussian function (GF) for image smoothing

The first step of the ICED is image smoothening using the GF. It reduces the noise influence present in the images due to factors such as image acquisition equipment, compression and decompression operations. Here, the two-dimensional GF is used to filter the contrast-enhanced Microscopic Images.

4.3.4.2 Gradient computation

Next, the gradient magnitude and the direction of an microscopic images are estimated. It uses a first-order partial difference in 2*2 neighborhoods of each pixel point.

4.3.3.3 Non-maximum suppression

This step is to obtain accurate position and unilateral edges. This method selects the edge points by judging whether or not the gradient magnitude along with the gradient direction of all pixels, is maximum within its neighboring pixels.

4.3.3.4 Double threshold selection

A ICED adopts the double threshold approach for detecting and connecting edge points after performing the non-maximum suppression. The adopted technique has two threshold values: higher and low. The pixels are marked as edge points when their gradient magnitude is greater than the higher threshold, and the pixels are marked as non-edge points when their gradient magnitude is below the lower threshold. After this procedure, the outcome of edge detection is discontinuous. The remaining points connected with the edge points are also marked as edge points to acquire continuous edges. Likewise, the ICED technique detects the edges in the microscopic images.

4.3.4 Comparison Results Of Sobel, Laplacian And ICED

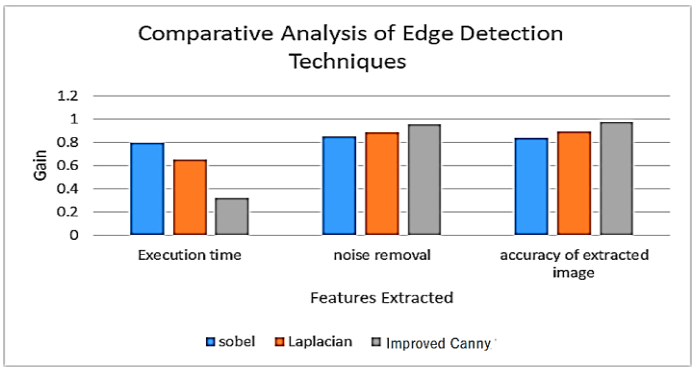

Figure 8: Analysis of Different Edge Detection Algorithm

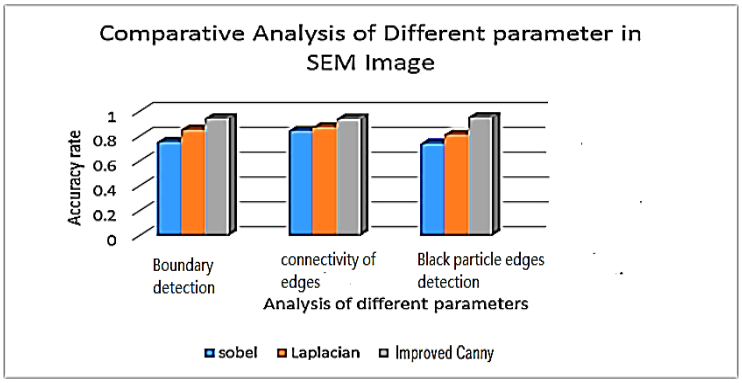

Figure 9: Object based Analysis of Microscopic images

Figure 8 and 9 depicits that sobel is not able to differentiate white and black pixels at the boundary side and Laplacian is not identifying the black pixels. Sobel detector cannot produce accurate edge detection with thin and smooth edge. ICED connects the neighbour good pixels as strong edges and the connectivity of pixels is best. The execution time of ICED is less than 0.4 seconds for any microscopic images. ICED gives good accuracy rate in forming edges and gives good separation of white and black pixels even at the boundary side also.

4.4 To estimate the tensile strength with the effect of particle orientation in microscopic images using Adaptive Density-based Spatial Clustering of Application with Noise (ADBSCAN) algorithm

An automated microscopic image analysis method with the help of image orientation detection is proposed using the Adaptive Density-based Spatial Clustering of Application with Noise (ADBSCAN) clustering algorithm. The detection of image orientation using the proposed approach helps to find out the material strength of Black Particles (BPs). Here, the images of eggshell powder with 200-micron meters having

different weights, such as 1%, 2%, 3%, 4%, and 5%, are taken as input. Afterwards, pre-processing is carried out in which noise removal using Cosine Distance induced Bilateral Filter (CD-BF) is performed. Then, the image's contrast is enhanced through the gaussian distribution adapted contrast limited adaptive histogram equalization (GD-CLAHE) technique. Next, the Improved canny edge detector (ICED) is used, followed by Segmentation with Threshold-based Otsu (T-Otsu) segmentation. Finally, clustering takes place ADBSCAN model. After that, quantitative analysis is done using Gaussian, scatterplot, and histogram for all weight percentages. The outcomes revealed that the proposed work computes the orientation more accurately and effectively estimates the material strength of the eggshell powder which is shown in Figure 3.

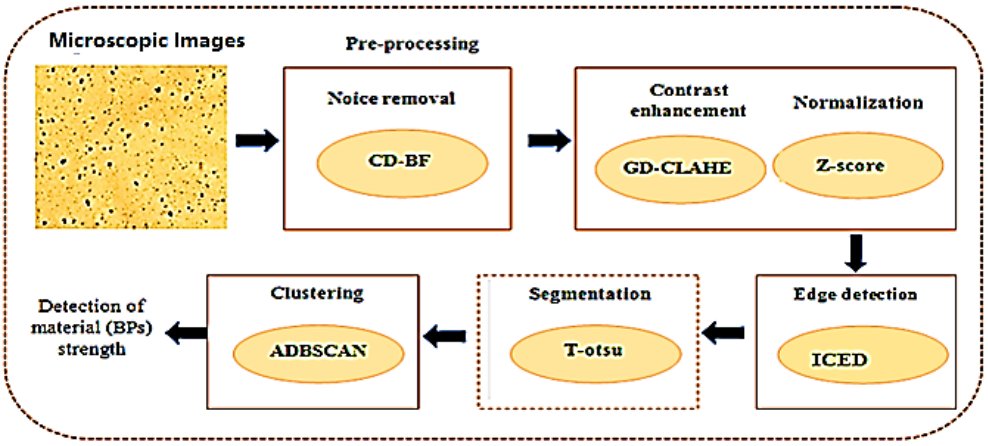

Figure 10: Research Methodology for estimation of particle orientation.

Figure 10 explains the microscopic images of eggshell powders (200-micron meters) with different weights are taken as input and are preprocessed. CD-BF approach to reduce the noise level of the image. CD computes the similarity of the pixels more effectively, even when two similar pixels are far apart in an image. GD-CLAHE is utilized to enhance the microscopic image's contrast level. Contrast Limited Adaptive Histogram Equalization (CLAHE) is a modified form of adaptive histogram equalization, which is applied to the overall neighborhood pixels of an image and derives the transformation function. the Gaussian Distribution (GD) function is used as the variation for clip limit. This modification process of clip limit in conventional CLAHE is termed Gaussian distribution adapted CLAHE (GD-CLAHE). The ICED detailed explanation is given in 4.3. After edge detection, BPs in the edge-detected microscopic image are segmented using the T-Otsu segmentation technique. Otsu segmentation is used because it has effortless calculation, is robust, and is adaptable to various applications.

After segmentation, the ADBSCAN clustering technique identifies the characterization of the BPs in the segmented images. If the particles in the clusters are evenly distributed, then the materials (BPs) are in good strength. Otherwise, they are overlapped and indicate the poor strength of the BPs. DBSCAN is a density-based clustering technique where clusters are identified by looking at the density of points. The clusters discovered by an algorithm are considered regions in the space that is dense in pixels. It requires two parameters to determine the cluster assignments by assessing the local density at each pixel: distance radius and a minimum number of pixels. Distance radius defines the neighborhood around a data point; the minimum number of pixels indicates the number of neighbors within the distance radius. However, sometimes due to the improper calculation based on Euclidean Distance, several valid objects are miscalculated as noise points. Therefore, the Euclidean distance in the DBSCAN technique is replaced with the Manhattan distance for maximizing the number of objects in the smallest effective cluster. With this help, clustering parameters are identified optimally so that superior clustering outcomes can be attained. This adoption of Manhattan distance in the conventional DBSCAN is called ADBSCAN.

4.4.2 Results and Discussion

4.4.2.1 Estimation of Tensile strength using Particle Orientation

Figure 11 depicits the orientation is computed based on the segmented BPs. To improve the accuracy of orientation detection of BPs, they are segmented effectively.

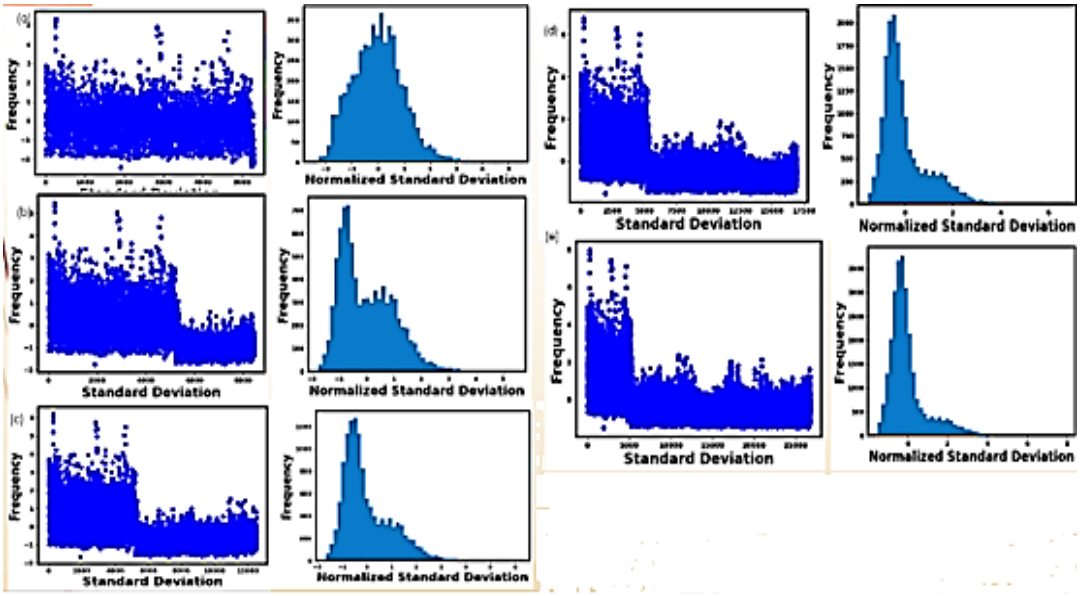

Figure 11: Statistical Analysis of tensile strength through particle orientation of different wt.% from 1 to 5.

If the BPs in the eggshell powder distribute evenly, then the strength of the eggshell powder is good and can be used for various applications. On the other hand, if high agglomeration is present and the particles are not evenly distributed, the material is not so good. It can be broken very quickly and is not suitable for further process. As the weight value increases, the number of agglomerations increases. The higher agglomeration in the particle reveals the poor material strength of eggshell powder. The orientation is also plays a vital role in the material strength and the automated method given solution for orientation estimation also.

5. RESEARCH FINDINGS

The following conclusions are arrived based on the research work

i. In this work first a novel automated microstructure image analysis method has been developed to explore the quantitative observations from the optical imaging technique. The modified k-means clustering algorithm used to predict the actual particle size based on the reference scale used in the optimal images. It worked well far away points and boundaries pixel point which brings into clusters. The pixel outliers were completely avoided. The statistical analysis was predicted accurately and quantitatively. Statistical analysis established that the left and right mean values for varying wt.% of the fillers were the important parameters, which directly influenced the tensile strengths of the composites. The values of tensile strength in experimental were closely predicted to the models and accuracy was found. Through developed automated microstructure image analysis method is able to study the connection between structure property and its behavior i.e., the shape and even particle distribution.

ii. Next the quantitative assessment of particle dispersion in polymeric composites and its effect on mechanical properties such as Tensile strength, agglomeration effect and particle orientation were analyzed. Using automated image analysis method, we have analyzed the optical images of the spent coffee bean powder (SCBP) reinforced polypropylene carbonate (PPC) polymer composites with varying wt.% of the filler (5%,10%,15%, and 20%). Statistical analysis of the microstructures reveals that the distribution of clusters is bi-modal and also shows the possibility of ‘clustering of clusters’ along with the ‘clustering of particles’. A microstructure-sensitive effective volume fraction is proposed to account for the effect of agglomeration on mechanical properties.

iii. Next the best edge detection for microstructure images orientation were analyzed. In our work chosen three important edge detection algorithms such as sobel. Laplacian and Improved Canny Edge detection (ICED) and compared the results and found best detection algorithm. ICED is the best algorithm to detect edges and orientation of microstructure images

iv. Next the microstructure image orientations are estimated using newly developed automated image analysis method to predict material strength and behaviour using the ADBSCAN clustering algorithm. The proposed work comes under the following steps, pre-processing, contrast enhancement via GD-CLAHE, edge detection with ICED, segmentation by T-Otsu, and finally, clustering through ADBSCAN. The clustering results of the proposed technique are analyzed to verify its effectiveness. From the analysis, it is apparent that the proposed technique computes the orientation more accurately and estimates the material strength of the eggshell powder. The particle distribution can determine the material strength during clustering. The even distribution of BPs during clustering shows a better strength of the particles. However, uneven distribution reveals the poor strength of the eggshell powders. Thus, the proposed ADBSCAN clustering technique effectively achieves this particle distribution. Hence, it is clear that the proposed model achieves accurate results and overcomes the problem of misidentification of experts by using their naked eyes.

6. ORGANIZATION OF THESIS

The research work carried out in this dissertation is organized as follows.

Chapter 1, explains the fundamental concepts Image processing techniques, various Machine Learning algorithms, Microscopic Images importance, Influence of statistical analysis and its need for the study and problem statement. The objectives of the research work and organization of the thesis are also outlined in this chapter.

Chapter 2 comprises a literature study of various research papers. It reviews the various application of image processing in emerging world. A detailed study on Microscopic images, its fundamental works and its applications were reviewed. The different types of machine learning algorithms such as k-means clustering, DBSCAN clustering algorithm for orientation were most studied. For getting an accurate result, different types of statistical analysis were studied.

Chapter 3, a proposed The Egg Shell Powder (ESP) reinforced polypropylene carbonate (PPC) polymer composites with differing wt. percent of the filler was therefore considered for analysis. A predicted tensile strength model has been developed relating the statistical parameters with the tensile strength. Depending on the result, a close agreement was found between the experimental findings and the model for the tensile strength of the composites with differing wt. percent of the filler reinforcement.

In Chapter 4, a proposed establish quantitative correlations between the particle/cluster size distribution and the mechanical properties of particle reinforced polymer composites (PRPC). The detailed statistical analysis of the microstructure and the proposed effective volume fraction helps to develop a deeper quantitative understanding of the PRPC than the conventional qualitative correlation of microstructural features with the properties and failure processes

In Chapter 5, a proposed edge detection importance for orientation analysis chosen three algorithms such as Sobel, Laplacian gradient based and Improved Canny Edge detection algorithm (ICED). Finally, compared three algorithms for good edge detection and found ICED algorithm provides good results in various parameters such as fast execution time and noise reduction in Microscopic images.

In Chapter 6, an automated Microscopic analysis with the help of image orientation detection is proposed using the Adapted Density-based Spatial Clustering of Application with Noise (ADBSCAN) clustering algorithm. The detection of image orientation using the proposed approach helps to find out the material strength of black particles. Finally, clustering takes place ADBSCAN model. After that, quantitative analysis is done using Gaussian, scatterplot, and histogram for all weight percentages. The outcomes revealed that the proposed work computes the orientation more accurately and effectively estimates the material strength of the eggshell powder.

In Chapter 7, concludes a development of automated microscopic image anlysis method for the statistical analysis of different Microscopic images. It is planned to expand the proposed automated image analysis method in future as the concept of reinforcement learning of machine learning. Various algorithms will be implemented such as Deep Q Network (DQN), Deep Deterministic Policy Gradient (DDPG), Asynchronous Advantage Actor-Critic Algorithm (A3C), Q-Learning with Normalized Advantage Functions (NAF) etc. Finally, this algorithm results were compared in quantitative analysis.

REFERENCES

1. Moein Mozaffarzadeh, Eric Verschuur, Martin D. Verweij, Verya Daeichin, Nico De Jong and Guillaume Renaud, Refraction-Corrected Transcranial Ultrasound Imaging Through the Human Temporal Window Using a Single Probe, *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, **69** (4), (2022), 1191 – 1203.
2. Alexandre Calapez, Agostinho Rosa, A Statistical Pixel Intensity Model for Segmentation of Confocal Laser Scanning Microscopy Images, *IEEE Transactions on Image Processing*, **19** (9), (2010), 2408 – 2418.
3. Pengfei Song, Armando Manduca, Joshua D. Trzasko, Ronald E. Daigle and Shigao Chen , On the Effects of Spatial Sampling Quantization in Super-Resolution Ultrasound Microvessel Imaging, *Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, **65** (12), (2018), 2264 – 2276.
4. Codruta O. Ancuti, Cosmin Ancuti, Christophe De Vleeschouwer and Mateu Sbert, Color Channel Compensation (3C): A Fundamental Pre-Processing Step for Image Enhancement, *IEEE Transactions on Image Processing*, **29** (1), (2019), 2653 – 2665.
5. W. Wang, I. Pollak, T.-S. Wong, C.A. Bouman, M.P. Harper and J.M. Siskind Hierarchical Stochastic Image Grammars for Classification and Segmentation, *IEEE Transactions on Image Processing*, **15** (10), (2006), 3033 – 3052.
6. Lea Melki, Melina Tourni and Elisa E. Konofagou, Electromechanical Wave Imaging with Machine Learning for Automated Isochrone Generation, *IEEE Transactions on Medical Imaging*, **40** (9), (2021), 2258 – 2271.
7. Hossein Aghighi, Mohsen Azadbakht, Davoud Ashourloo, Hamid Salehi Shahrabi and Soheil Radiom, Machine Learning Regression Techniques for the Silage Maize Yield Prediction Using Time-Series Images of Landsat 8 OLI, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* , **11** (12), (2018), 4563 – 4577.
8. Farhan Ullah, Bofeng Zhang and Rehan Ullah Khan, Image-Based Service Recommendation System: A JPEG-Coefficient RFs Approach, *IEEE Access*, **8** (1), (2019), 3308 – 3318.

9. Satoru Ueda, Yoshio Kobayashi, Satoshi Koizumi and Yasuyuki Tsutsumi, In situ observation of water in a fuel cell catalyst using scanning electron microscopy, *Microscopy*, **64** (2), (2015), 87 – 96.
10. Yukihito Kondo, Eiji Okunishi, Magnified pseudo-elemental map of atomic column obtained by Moiré method in scanning transmission electron microscopy, *Microscopy*, **63** (5), (2014), 391 – 395.
11. Max Mignotte, Segmentation by Fusion of Histogram-Based K-Means Clusters in Different Color Spaces, *IEEE Transactions on Image Processing* **17** (5), (2008), 780 – 787.
12. Yelghi Aref, KoSe Cemal, Yelghi Asef and Shahkar Amir, Automatic fuzzy-DBSCAN algorithm for morphological and overlapping datasets, *Journal of Systems Engineering and Electronics*, **31** (6), (2020), 1245 – 1253.
13. Hongfu Xie, Jiecun Liang, Zhen Wang, Minghui Liao and Xide Li, Scanning Imaging Restoration of Moving or Dynamically Deforming Objects, *IEEE Transactions on Image Processing*, **29** (2), (2020), 7290 – 7305.
14. Jing Su and Jing Li, Show Auto-Adaptive and Tell: Learned From the SEM Image Challenge, *IEEE Access*, **9** (1), (2021), 51494 – 51500.
15. Mihai-Virgil Nichita, Maria-Alexandra Paul, Vladimir-Alexandru Paun and Viorel-Puiu Paun, Image Clustering Algorithms to Identify Complicated Cerebral Diseases. Description and Comparison, *IEEE Access*, **8** (2), (2020), 88434 – 88442.
16. Yo-Ping Huang, Pritpal Singh and Hung-Chou Kuo, A Hybrid Fuzzy Clustering Approach for the Recognition and Visualization of MRI Images of Parkinson's Disease, *IEEE Access*, **8** (1), (2020), 25041 – 25051.

LIST OF PUBLICATIONS

1. G. Elizabeth Rani, R.Murugeswari, SuchartSiengchin, N.Rajini and M. Arul Kumar, Quantitative Assessment of Particle Dispersion in Polymeric Composites and its Effect on Mechanical Properties, *Journal of Material Research and Technology*, **19** (1), (2022), 1836-1845.

2. G. Elizabeth Rani, R.Murugeswari and N.Rajini, A Detection of Material Strength of Composite Eggshell Powders with an Analysis of Scanning Electron Microscopy, *Bulletin of Materials Science*, BOMS-D-22-00305.

3. G.Elizabeth Rani, R.Murugeswari, Selvakumar Vairamuthu, N.Rajini, Faruq Mohammad, Suchart Siengchin, Sikiru O.Ismail and K.Senthilkumar, An Automated Software Development for Analysis of the Morphological-Tensile Property Relationship in Egg Shell Bio-based Particulate Composites using Machine Learning Algorithms , *Composites Part C,* **10** (1), (2023), 1-12.

4. G. Elizabeth Rani, R.Murugeswari and N.Rajini Edge Detection in Scanning Electron Microscope (SEM) Images using Various Algorithms, *2020 4th International Conference on Intelligent Computing and Control Systems, IEEE Explorer*, (2020), 401-405.